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LINOPT: A FORTRAN ROUTINE FOR SOLVING LINEAR PROGRAMMING PROBLE--ETC(U)

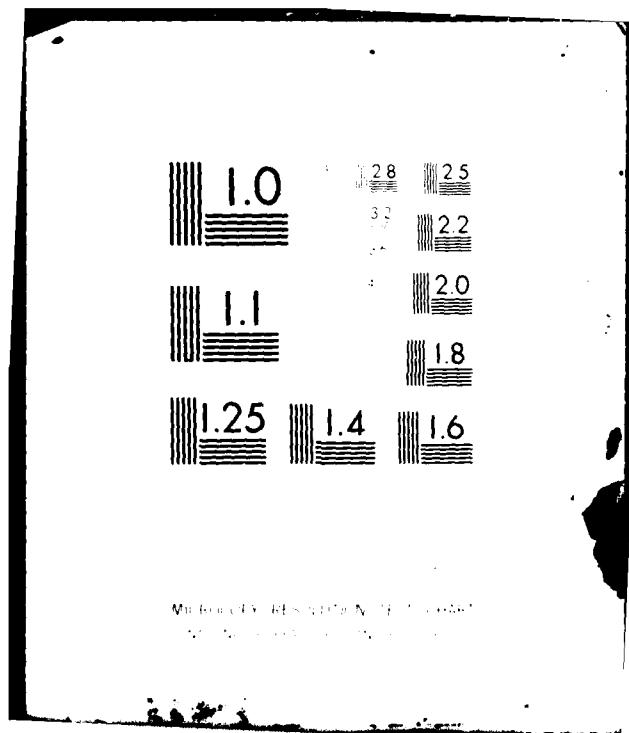
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**LINOPT, A FORTRAN ROUTINE FOR SOLVING  
LINEAR PROGRAMMING PROBLEMS**

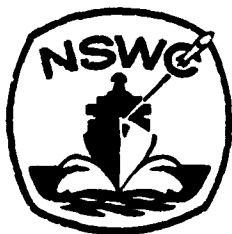
BY JOHN W. WINGATE

RESEARCH AND TECHNOLOGY DEPARTMENT

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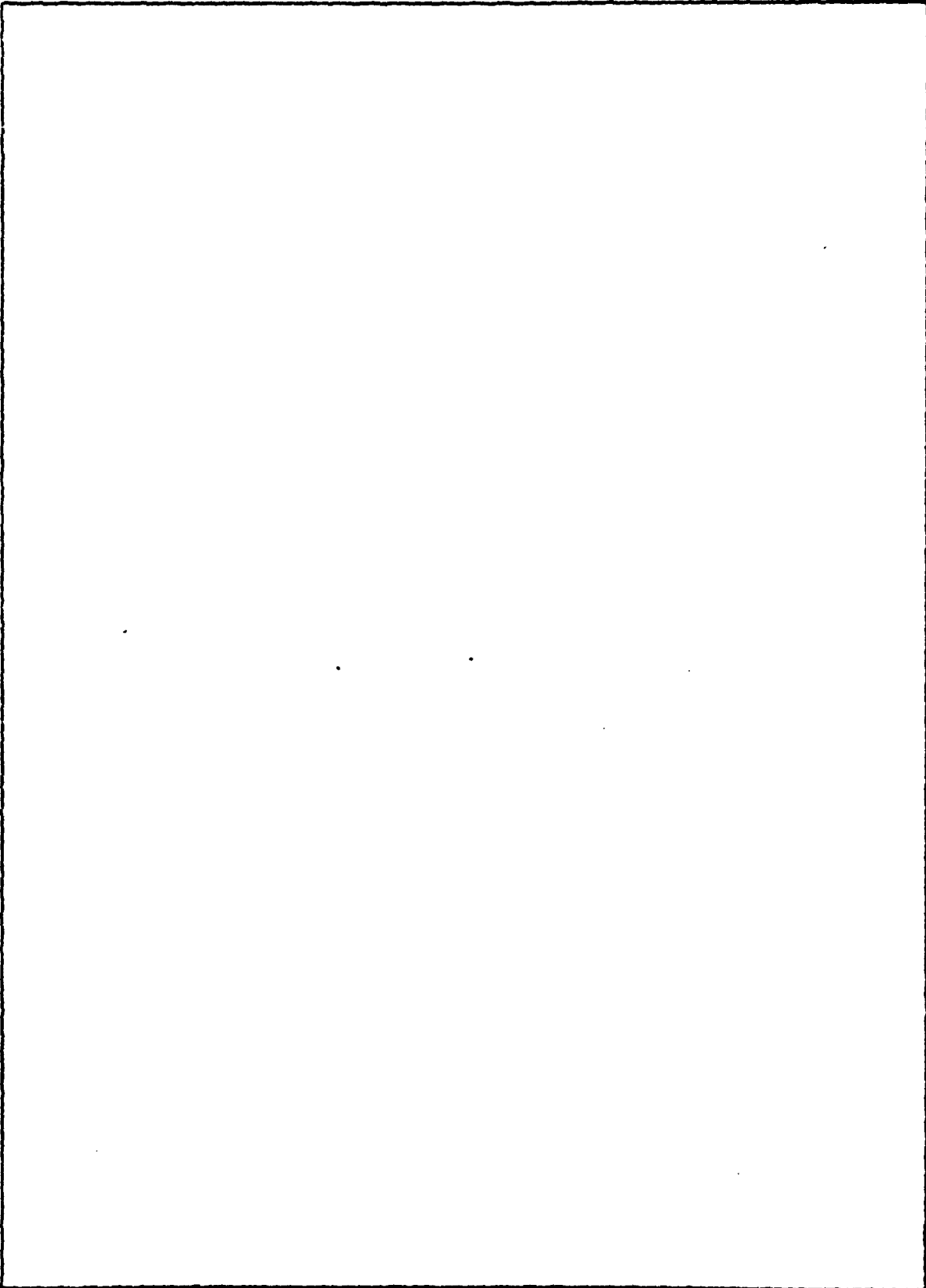
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## CHAPTER 1

## INTRODUCTION

REPORT ORGANIZATION

This report documents a FORTRAN subroutine (with associated subroutines) called LINOPT for solving linear programming (LP) problems. It is divided into several chapters. Following the INTRODUCTION is a chapter (PROBLEM FORMAT AND PROGRAM USE) explaining the types of problems which can be solved by LINOPT, some manipulations on them and correspondences with program notation. A chapter (SUPPORT FUNCTIONS AND DUALITY IN LINEAR PROGRAMMING) discusses some of the duality concepts behind the formulation and solution of LP problems. The next chapter, DUAL SIMPLEX METHOD gives some information about the algorithm used in the program. EXAMPLES and a LISTING follow.

PROBLEM FORMULATION

A rather abstract formulation of an LP problem in the following: Let  $X$  be a real vector space paired with  $M$  under the bilinear form (inner product)  $(\mu, x) \rightarrow \mu \cdot x$ ,  $\mu \in M$ ,  $x \in X$ , and let  $Y_i$ ,  $i = 1, \dots, m$  be similarly paired with  $\Lambda_i$ ,  $i = 1, \dots, m$ . Given  $\mu \in M$ , closed convex sets  $C_i$  in  $Y_i$ , and linear transformations  $A_i : X \rightarrow Y_i$ ,  $i = 1, \dots, m$ ,

$$\begin{aligned} &\text{maximize} \quad \mu \cdot x \\ &\text{subject to} \quad A_i x \in C_i, \quad i=1, \dots, m. \end{aligned}$$

This problem in convex programming has the following as its dual problem:

$$\begin{aligned} &\text{minimize} \quad \sum_{i=1}^m \sigma_{C_i}(\lambda_i) \\ &\text{subject to} \quad \sum_{i=1}^m A_i^* \lambda_i = \mu \end{aligned}$$

where  $\sigma_{C_i}$  is the support function of the set  $C_i$  — see Chapter 3 for more on support functions. For explanatory purposes it is sufficient to take each  $A_i$  equal to the identity, so that  $Y_i = X$ ,  $\Lambda_i = M$ ,  $i = 1, \dots, m$ . Chapter 3 treats this simplified version.

The program LINOPT is set up to handle constraints of the form  $\mu_i \cdot x \in C_i$  where  $\mu_i \in M$  and  $C_i$  is a nonempty closed interval. If some  $C_i$  is a bounded interval of nonzero length, the dual problem has a nonlinear objective; it is, however, convex and piecewise linear. The details are given in Chapter 2, where it is shown that the general form of the dual objective is the sum of two terms, one linear, and one a weighted  $\ell_1$  norm.



The algorithm used in the program is a form of the revised dual simplex algorithm modified to handle upper and lower bound constraints. The inverse matrix used is a row-basis inverse. Accordingly, the algorithm is more efficient on problems with many constraints. (On problems with fewer dependent variables than independent variables, a column-basis inverse would be smaller.) Use of a row basis has definite advantages in modifying a problem and then reoptimizing.

No new theory is involved in this program. The dual simplex algorithm can be found in standard linear programming texts.<sup>1,2</sup> Insisting that all variables in the primal problem have both upper and lower bounds makes it trivial to find a dual-feasible point to start the algorithm, and because of the resulting asymmetry between primal and dual problems, allows us to handle directly (via the dual problem) certain piecewise linear convex minimization problems.

The results from convex analysis used in Chapter 3 can be found in greater generalization and detail in Rockafellar's book.<sup>3</sup>

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<sup>1</sup>Hadley, G., Linear Programming, Addison-Wesley, Reading, 1962.

<sup>2</sup>Simmonard, M., Linear Programming, Prentice-Hall, Englewood Cliffs, 1966.

<sup>3</sup>Rockafellar, R. T., Convex Analysis, Princeton University Press, Princeton, 1970.

## CHAPTER 2

## PROBLEM FORMAT AND PROGRAM USE

INTRODUCTION

LINOPT is programmed to solve a problem maximizing (or minimizing) a linear function subject to upper and lower bounds on linear constraint functions. (The bounds are equal for an equality constraint.) The dual to this problem has a piecewise linear objective function and linear equality constraints. Missing bounds in the primal problem correspond to sign constraints on the dual variables. Such missing bounds can be handled by introducing a penalty function for the sign constraint violations in the dual problem. An even simpler and more direct interpretation is that the missing bounds can be replaced by bounds so large in magnitude that they are effectively infinite.

PRIMAL PROBLEM

Maximize  $x_{k_0}$  subject to  $\underline{b}_k \leq x_k \leq \bar{b}_k$ ,  $k=1, \dots, m+n$ , where  $k_0 \in \{1, \dots, m+n\}$  and

$$x_{n+i} = \sum_{j=1}^n a_{ij} x_j, \quad i=1, \dots, m.$$

The objective variable  $x_{k_0}$  can be expressed by:

$$x_{k_0} = \sum_{j=1}^n c_j x_j,$$

where

$$c_j = \begin{cases} \delta_{k_0 j} & \text{if } k_0 \leq n, \\ a_{k_0-n, j} & \text{if } k_0 > n. \end{cases}$$

The same data also define the dual problem.

DUAL PROBLEM

Minimize  $\sum_{k=1}^{m+n} \max \{u_k \underline{b}_k, u_k \bar{b}_k\}$  subject to

$$u_j + \sum_{i=1}^m u_{n+i} a_{ij} = c_j, \quad j=1, \dots, n.$$

The dual objective has another form which is more likely to be recognized in an application:

$$\sum_{k=1}^{m+n} \max \{u_k \underline{b}_k, u_k \bar{b}_k\} = \sum_{k=1}^{m+n} \left( \frac{\bar{b}_k + \underline{b}_k}{2} \right) u_k + \sum_{k=1}^{m+n} \left( \frac{\bar{b}_k - \underline{b}_k}{2} \right) |u_k|$$

Thus the dual objective contains a linear term and a weighted  $\ell_1$ -norm term.

The dual variable  $u_k$  can be thought of as a Lagrange multiplier for the constraint  $x_k \in [b_k, b_k]$ .

#### MISSING BOUNDS; SIGN CONSTRAINTS

The following table (TABLE 1) shows how to prepare primal problems with missing constraints or dual problems with sign constraints.  $M$  is a very large positive number. (The default value supplied by the program is  $10^{100}$ .) The first line of the table gives the standard two-sided constraint assumed by the program. The other lines give the modifications for unilateral and no constraints. In the modified problem  $u_k$  is always unconstrained in sign. The dual objective picks up the original linear term when the sign constraint is satisfied, and a penalty term when the sign constraint is violated.

When the program gives an optimal solution in which  $x_k = \pm M$  for some  $k$ , the original problem has an unbounded solution. If it has a finite solution, the program will yield it, and it will not depend on  $M$  (unless  $M$  has been set so small that it interferes with the "legitimate" constraints). The calculations are arranged so that roundoff errors due to the disparity in magnitude between  $M$  and the original data do not propagate from iteration to iteration, and appear within an iteration only if some  $x_k = \pm M$ .

The objective variable  $x_{k_0}$  is also formally a constrained variable, although generally the constraint will be  $-M \leq x_{k_0} \leq M$ , i.e. essentially no constraint at all. Tighter bounds may at times be useful. The constraint  $b_{k_0} \leq x_{k_0} \leq M$  can be used to answer the question: Is  $\max x_{k_0} \geq b_{k_0}$ ? If the answer to this question is negative, the constraints are inconsistent. As soon as the inconsistency is detected, the program returns to the calling program without going on to calculate the solution completely.

TABLE 1 FILLING IN MISSING BOUNDS

Original constraints on $x_k$	Original sign constraints on $u_k$	Original dual objective term	Modified constraints	Modified dual objective term
$\underline{b}_k < x_k < \bar{b}_k$	$u_k$ unconstrained in sign	$\max\{u_k \underline{b}_k, u_k \bar{b}_k\}$	$\underline{b}_k < x_k < \bar{b}_k$	$\max\{u_k \underline{b}_k, u_k \bar{b}_k\}$
$x_k < \bar{b}_k$	$u_k \geq 0$	$u_k \bar{b}_k$	$-M < x_k < \bar{b}_k$	$\max\{u_k(-M), u_k \bar{b}_k\}$
$x_k > \underline{b}_k$	$u_k \leq 0$	$u_k \underline{b}_k$	$\underline{b}_k \leq x_k \leq M$	$\max\{u_k \underline{b}_k, u_k M\}$
$x_k$ unconstrained	$u_k = 0$	0	$-M \leq x_k \leq M$	$M u_k $

PROGRAM NOTATION

Correspondence between the notation herein and the notation of LINOPT is given in Table 2.

TABLE 2 CORRESPONDING VARIABLES

This TR	LINOPT
m	M
n	N
k <sub>0</sub>	IOBJ
x <sub>k</sub>	X(K)
u <sub>k</sub>	U(K)
b <sub>k</sub>	BL(K)
b̄ <sub>k</sub>	BU(K)
a <sub>ij</sub>	A(ROW(I) + COL(J))
M	BIGM

The FORTRAN variable BIGM is included in the program for the user's convenience. It supplies a default value (which can be changed) for filling in the missing bounds. (The user must fill in all bounds, since there is no provision for keeping track of missing bounds otherwise.)

CONSTRAINT COEFFICIENT STORAGE

The constraint coefficients are referenced in an unusual but flexible way. Row and column pointer arrays ROW and COL are used to index an array A. The FORTRAN standard for array storage is by columns (a<sub>11</sub>, a<sub>21</sub>, a<sub>31</sub>, ..., a<sub>12</sub>, a<sub>22</sub>, a<sub>32</sub>, ..., etc.) Suppose that we have a matrix A stored in an array dimensioned 10 x 20 and we wish to study a problem whose constraint coefficients form a submatrix of A, as in

$$\begin{bmatrix} y_5 \\ y_8 \end{bmatrix} = \begin{bmatrix} a_{57} & a_{53} & a_{59} \\ a_{87} & a_{83} & a_{89} \end{bmatrix} \begin{bmatrix} z_7 \\ z_3 \\ z_9 \end{bmatrix}$$

We can set  $x_1 = z_7$ ,  $x_2 = z_3$ ,  $x_3 = z_9$ ,  $x_4 = y_5$ ,  $x_5 = y_8$ ,

$$\begin{aligned} \text{ROW}(1) &= 5, \text{ROW}(2) = 8, \\ \text{COL}(1) &= 60, \text{COL}(2) = 20, \text{COL}(3) = 80. \end{aligned}$$

COL(J) is set to the number of elements in the array preceeding the coefficient column for X(J)— 6 x 10 for the 7th column, 2 x 10 for the 3rd and 8 x 10 for the 9th. ROW(I) then picks off the appropriate entry in the column. We can even introduce (by using the LOCF function) columns extraneous to the array storing A. Consider the modified example:

$$\begin{bmatrix} y_5 \\ y_8 \end{bmatrix} = \begin{bmatrix} a_{57} & a_{53} \\ a_{87} & a_{84} \end{bmatrix} \begin{bmatrix} z_7 \\ z_3 \end{bmatrix} + \begin{bmatrix} b_{54} \\ b_{84} \end{bmatrix} w_4$$

in which  $x_3 = w_4$ . COL(3) is set by

$$\text{COL}(3) = \text{LOCF}(\text{B1}, 4) - \text{LOCF}(\text{A}(1, 1)).$$

The columns of B must be structured the same way as the columns of A for this procedure to work. Instead of having a coefficient matrix stored in the array in the usual way we could have it transposed, perhaps as a result of starting with a dual problem. This corresponds to storage by rows (not the FORTRAN standard). A little reflection indicates that defining ROW the way COL is defined above, and COL the way ROW is defined handles this storage arrangement. Further examples are given in the program comments.

#### INPUT AND OUTPUT

Input and output variables are clearly indicated in the program comments. (The program is listed in the section titled "LISTINGS".) Arrays are passed as formal parameters. Scalars are passed by using a labelled common block /XXXLP/, which must accordingly be a common block in the calling program.

#### ROUND OFF CONTROL

In the program there are three input variables which can be used to control roundoff error accumulations. EPS is a tolerance used in checking constraint violations. H is also used to zero out coefficients in the tableau which have small nonzero values (typically for a CDC 60-bit machine, on the order of  $10^{-14}$ ) which ought to vanish. Finally constraint violations less than EPS are eliminated from the optimal solution before returning. For small problems EPS = 0 is generally all right.

The other roundoff - controlling variables are invert (a logical variable) and ITMAX. When INVERT is TRUE the inverse matrix corresponding to the current key K is calculated. ITMAX is a limit on the number of iterations. When this limit is reached control is returned to the calling LINOPT again with INVERT = TRUE., one may control the building of roundoff error in the inverse matrix (which otherwise is updated by column operations every iteration). (For small problems this may not be necessary.)

After obtaining a solution (or after any return from an initial call to LINOPT) INVERT can be set to FALSE for another call to LINOPT. Certain modifications to the problem data are permissible at such a time - constraints may be added, for example. These modifications are any for which the inverse matrix would be unchanged, and include the following (Note: primary indices: K(1), ..., K(N); secondary K(N + 1), ..., K(N + M) - see Chapter 4.)

#### ADDING CONSTRAINTS

M is increased, new elements to ROW are added to point to the new constraint coefficients (which, if not already defined should be stored appropriately), and new bounds added to BL and BU.

MODIFYING CONSTRAINTS

Bounds for any secondary variable can be changed. Inactive bounds for primary variables can be changed. Active bounds for primary variables can be changed, provided the corresponding solution is also changed; e.g. if  $X(K(1)) = BU(K(1))$  and  $BU(K(1))$  is changed,  $X(K(1))$  must be changed in the same way. Constraint coefficients for dependent variables  $X(N + 1), \dots, X(N + M)$  which are also secondary variables can be changed; (these may include the objective variable) or such constraints can be dropped, with appropriate changes to ROW, M, BL and BU. (If the constraint corresponding to ROW(I) is dropped, the simplest way to make these changes is to set  $ROW(I) = ROW(M)$ ,  $BL(N + I) = BL(N + M)$ ,  $BU(N + I) = BU(N + M)$ , and then  $M = M - 1$ , so that the indexing for  $X(N + M)$  is changed to  $X(N + I)$ ).

Of course, when LINOPT is recalled with INVERT = TRUE, any problem changes whatsoever are permissible.

## CHAPTER 3

## SUPPORT FUNCTIONS AND DUALITY IN LINEAR PROGRAMMING

The support function  $\sigma_C$  of a convex set  $C$  in  $X$  is a convex function defined on  $M$  by:

$$\sigma_C(\mu) = \sup_{x \in C} \mu \cdot x \quad (1)$$

The support function of the empty set is  $-\infty$  everywhere. For nonempty  $C$ ,  $\sigma_C(\mu) > -\infty$  and may take the value  $+\infty$ ; in Rockafellar's terminology, it is a proper convex function<sup>4</sup>.

Many of the formulas of convex analysis can be simplified when they are restricted to convex polyhedra and convex polyhedral functions. One such is found in Corollary 16.4.1 of Rockafellar's book<sup>5</sup>, from part of which we can derive the following: Let  $C_1, \dots, C_m$  be closed convex polyhedra with nonempty intersection  $C$  (also a convex polyhedron). Then

$$\sigma_C(\mu) = \begin{cases} \min \sum_{i=1}^m \sigma_{C_i}(\mu_i) \\ \text{subject to } \sum_{i=1}^m \mu_i = \mu \end{cases} \quad (2)$$

(The general version of the corollary is required if  $C$  is empty.) Rockafellar terms the operation in (2) "infimal convolution", since for  $m = 2$ ,  $\sigma_{C_1 \cap C_2}(\mu) = \inf_{\lambda} (\sigma_{C_1}(\lambda) + \sigma_{C_2}(\mu - \lambda))$  a form reminiscent of integral convolutions. Formulas (1) and (2) express  $\sigma_C(\mu)$  as the common optimal value of a pair of dual convex programming problems:

Primal Problem:

Maximize  $\mu \cdot x$

subject to  $x \in C_i, i=1, \dots, m.$

Dual problem:

Minimize  $\sum_{i=1}^m \sigma_{C_i}(\mu_i)$

subject to  $\sum_{i=1}^m \mu_i = \mu.$

4. Ibid, p. 24.

5. Ibid, p. 146.



Three solution cases arise:

1.  $\sigma_C(\mu) = -\infty$ :  $C$  is empty. The dual objective is unbounded below on the dual constraint set.
2.  $-\infty < \sigma_C(\mu) < +\infty$ :  $C$  is not empty. The optimal value, viz  $\sigma_C(\mu)$ , is attained in both problems.
3.  $\sigma_C(\mu) = +\infty$ :  $C$  is not empty. The primal objective is unbounded above on the primal constraint set. The dual objective is  $+\infty$  everywhere on the dual constraint set, (i.e.  $\sigma_{C_i}(\mu_i) < \infty$ ,  $i = 1, \dots, m \Rightarrow \sum_{i=1}^m \mu_i \neq \mu$ ).

Suppose that  $\sigma_C(\mu)$  is finite, and let  $x^*$  solve the primal,  $\mu_i^*$ ,  $i=1, \dots, m$ , the dual. Then

$$\begin{aligned}
 \sigma_C(\mu) &= \mu \cdot x^* && \text{(primal optimality)} \\
 &= \left( \sum_{i=1}^m \mu_i^* \right) \cdot x^* && \text{(dual constraint)} \\
 &= \sum_{i=1}^m (\mu_i^* \cdot x^*) \\
 &\leq \sum_{i=1}^m \sigma_{C_i}(\mu_i^*) && \text{(primal constraints)} \\
 &= \sigma_C(\mu) && \text{(dual optimality)}
 \end{aligned}$$

It follows that

$$\mu_i^* \cdot x^* = \sigma_{C_i}(\mu_i^*), \quad i=1, \dots, m, \quad (3)$$

or that  $\mu_i^*$  supports  $C_i$  at  $x^*$ :  $\mu_i^*$  is an outer normal to  $C_i$  at  $x^*$ . The formula is one way of expressing complementary slackness, since if  $x^* \in \text{int } C_i$  then  $\mu_i^* = 0$ , while

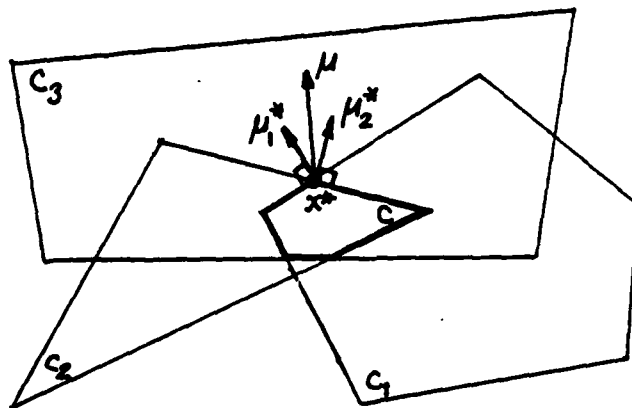


Figure 1 ILLUSTRATION OF DUAL OPTIMAL SOLUTIONS. ( $\mu_3^* = 0$ )

if  $\mu_1^* = 0$ , then the constraint  $x \in C_1$  can be dropped without altering the solution. The set of constraints for which  $\mu_1^* \neq 0$  are active (binding) at the optimum. (See Figure 1). There may be multiple solutions, each with a different set of active constraints.

The usefulness of (2) hinges on picking the constraint sets  $C_i$ ,  $i=1, \dots, m$ , to be simple enough to permit easy evaluation of their support functions. Any convex polyhedron can be expressed as the intersection of half-spaces, and any half-space can be defined by a linear inequality. Let  $H: = \{x: \mu \cdot x \leq b\}$ , where  $\mu \neq 0$ . Then

$$\sigma_H(v) = \begin{cases} ub & \text{if } v = u\mu \text{ and } u \geq 0, \\ +\infty & \text{otherwise.} \end{cases}$$

In terms entirely of hyperplane constraints the primal and dual problems become

Primal problem:

$$\begin{aligned} &\text{Maximize } \mu \cdot x \\ &\text{subject to } \mu_i \cdot x \leq b_i, \quad i=1, \dots, m \end{aligned}$$

Dual problem:

$$\begin{aligned} &\text{Minimize } \sum_{i=1}^m u_i b_i \\ &\text{subject to } \sum_{i=1}^m u_i \mu_i = \mu, \\ &\quad u_i \geq 0, \quad i=1, \dots, m. \end{aligned}$$

The sign constraints on  $u_i$  avoid infinite values of the dual objective and keep it linear so that both problems consist of optimizing linear functionals subject to linear constraints. Alternatively we could omit the sign constraints and keep the formulation in terms of support functions. This pair of problems also illustrates the more general duality relationship cited in the INTRODUCTION. Let  $A_1: X \rightarrow R$  be defined by  $A_1 X: = \mu_1 \cdot X$ . Then  $A_1^*: R \rightarrow M$  and  $A_1^* u = u \mu_1$ . Moreover,

$$\sigma_{(-\infty, b_1]}(u) = \begin{cases} ub_1 & \text{if } u \geq 0, \\ +\infty & \text{if } u \leq 0. \end{cases}$$

Thus the problems are expressible as:

Primal problem:

$$\begin{aligned} &\text{Maximize } \mu \cdot x \\ &\text{subject to } A_1 x \in (-\infty, b_1], \quad i=1, \dots, m \end{aligned}$$

Dual problem:

$$\begin{aligned} &\text{Minimize } \sum_{i=1}^m \sigma_{(-\infty, b_i]}(u_i) \\ &\text{subject to } \sum_{i=1}^m A_1^* u_i = \mu \end{aligned}$$

We may have two-sided constraints such as

$$\underline{b} \leq \mu \cdot x \leq \bar{b}$$

(where  $\underline{b} \leq \bar{b}$ ) defining a set  $S$  in  $X$ , which can be replaced by the pair of constraints

$$\begin{cases} \mu \cdot x \leq \bar{b}, \\ -\mu \cdot x \leq -\underline{b}. \end{cases}$$

since

$$\sigma_S(v) = \begin{cases} \max \{u\underline{b}, u\bar{b}\} & \text{if } v = u\mu, \\ +\infty & \text{otherwise,} \end{cases}$$

and  $\max \{u\underline{b}, u\bar{b}\}$  is nonlinear in  $u$  (unless  $\underline{b} = \bar{b}$ ), the dual of a problem with two-sided constraints is nonlinear. Of course it is easy to relate the two-sided and one-sided versions by using (2). Thus if  $u$  is the dual variable for the constraint  $\underline{b} \leq \mu \cdot x \leq \bar{b}$ ,  $u^+$  for  $\mu \cdot x \leq \bar{b}$  and  $u^-$  for  $-\mu \cdot x \leq -\underline{b}$ ,

$$\text{then} \quad u = u^+ - u^- \quad (4)$$

while if  $\underline{b} \neq \bar{b}$  either  $u^+$  or  $u^-$  vanishes (at the solution), so that

$$u^+ = \max \{u, 0\}, \quad -u^- = \min \{u, 0\}. \quad (5)$$

When  $\underline{b} = \bar{b}$ , only the difference  $u = u^+ - u^-$  is determined. An alternate viewpoint in this case is that  $u$  is the dual variable for the linear equality constraint  $\mu \cdot x = \bar{b}$ .

The pivoting operations of the dual simplex method can be thought of as substituting one hyperplane bounding a half-space for another, and consequently are better suited for the formulation in terms of one-sided constraints. The relations (4) and (5) and some sign bookkeeping then make it easy to apply the method to two-sided constraints. Explanations of the method without the sign manipulations are more transparent. Accordingly in the next section only one-sided constraints are considered.

## CHAPTER 4

## DUAL SIMPLEX METHOD

In the previous section no particular coordinates were used on  $X$ . Most LP problems encountered are expressed in terms of coordinates with respect to some particular basis for  $X$ , the coordinates then forming a set of independent variables. (as indicated previously, LINOPT assumes such a formulation.) Thus, with one-sided constraints, we get a pair of problems like the following, in which we assume that the  $n$  independent variables  $x_j$ ,  $j \in J$  are included in the  $m+n$  constrained variables  $x_k$ ,  $k \in K$ ; i.e.  $J \subset K$ .

Primal problem:

$$\begin{aligned} \text{Maximize } x_0 &= \sum_{j \in J} c_j x_j \\ \text{subject to } x_k &= \sum_{j \in J} a_{kj} x_j \leq b_k, \quad k \in K. \end{aligned}$$

(Note that  $a_{kj} = \delta_{kj}$  for  $k \in J$ .)

Dual problem:

$$\begin{aligned} \text{Minimize } \sum_{k \in K} u_k b_k \\ \text{subject to } \sum_{k \in K} u_k a_{kj} &= c_j, \quad j \in J \\ u_k &\geq 0, \quad k \in K. \end{aligned}$$

Note that the  $n$  equations relating the dual variables  $u_k$ ,  $k \in K$  can be written explicitly for  $u_j$ :

$$\sum_{i \in K \sim J} u_i a_{ij} + u_j = c_j$$

Thus in the dual problem,  $u_i$ ,  $i \in K \sim J$ , are independent and  $u_j$ ,  $j \in J$ , are dependent. Given some other subset  $J'$  of  $K$  for which  $x_j$ ,  $j \in J'$ , are linearly independent, we can transform the constraint relations so that  $x_j$ ,  $j \in J'$  are the independent variables through which the primal problem is phrased. Given such an index set  $J'$  we can define a corresponding basic solution. For  $J$  the definition of a basic solution is obtained by setting the independent variables  $x_j$ ,  $j \in J$ , and  $u_i$ ,  $i \in K \sim J$ , to their bounds and satisfying the constraint relations among the variables;  $\bar{x}_k$  and  $\bar{u}_k$  are the values of  $x_k$ ,  $u_k$  at the basic solution.

$\bar{x}_j = b_j$ , $j \in J$	(primary primal variables)
$\bar{x}_i = \sum_{j \in J} a_{ij} b_j$ , $i \in K \sim J$	(secondary primal variables)
$\bar{u}_j = c_j$ , $j \in J$	(secondary dual variables)
$\bar{u}_i = 0$ , $i \in K \sim J$	(primary dual variables)

The terms primary and secondary have been introduced instead of independent and dependent because one may wish to refer to the primary variables of the problem as initially formulated as the independent variables. The split between primary and secondary depends on the set  $J$  and changes with it. The secondary primal indices are usually called basic indices in linear programming texts, since they correspond to the indices for a column basis for the constraint matrix. This terminology is a little inappropriate here, since LINOPT makes use of a row basis corresponding to the complementary set of indices - the dual basic indices in the usual description. The use of "basic" in this sense is avoided here to prevent confusion.

Furthermore, in a problem with two-sided constraints the basic indices refer to the indexing of the equivalent one-sided problem, not the indexing of the two-sided problems, so that the basic variables for  $J$  would be  $x_k$  and  $-x_k$  for  $k \in K \setminus J$  and either  $x_j$  or  $-x_j$  (but not both) for  $j \in J$ . Alternatively we may retain the "primary/secondary" notation and supplement it with some way of indicating whether a primary variable is at its upper or its lower bound. (The program simply checks the solution value against the bounding values.)

In a basic solution the primary variables satisfy the constraints placed on them if all primal variables satisfy the constraints, the basic solution and  $J$  are primal-feasible. If the dual constraints are satisfied, the basic solution is dual-feasible. A basic solution which is both primal- and dual-feasible is optimal. At a basic solution both primal and dual objective variables have the value  $\sum_{j \in J} c_j b_j$ . The criterion for dual feasibility is simply that  $c_j \geq 0$ ,  $j \in J$ .

The transformation of the constraint coefficients accompanying a change from one set of primary variables to another can be performed explicitly when needed, or it can be expressed in terms of a nonsingular matrix relating the variables.

There are two ways of doing this. Let  $x_j$ ,  $j \in J$  and  $x_{j'}$ ,  $j' \in J'$  be two sets of primary primal variables. Set  $I = K \setminus J$ ,  $I' = K \setminus J'$ , and let  $x_j$  be a column vector whose entries are  $x_j$ ,  $j \in J$ , etc. Using matrix notation the two ways can be described as follows:

1. Solution for  $x_{I'}$

$$x_I = Ax_J \quad (A \text{ is } m \times n)$$

Rearrange columns to give:

$$B x_{I'} = R x_{J'}$$

with  $B$  a nonsingular  $m \times m$  submatrix of  $[I \ -A]$ . Then  $x_{I'} = B^{-1} R x_{J'}$ .

The columns making up  $B$  are a basis for the space spanned by the columns of  $[I \ -A]$

Applied to the dual:

$$\begin{aligned} U_I A + U_J &= C \\ U_I S + U_{J'} D &= C \\ U_I S D^{-1} + U_{J'} &= \bar{C}, \text{ where } \bar{C} = C D^{-1}. \end{aligned}$$

The rows of D form a basis for the space spanned by the rows of  $\begin{bmatrix} A \\ I \end{bmatrix}$ .

2. Solution for  $x_J$  and substitution:

$$\begin{bmatrix} x_I \\ x_J \end{bmatrix} = \begin{bmatrix} A \\ I \end{bmatrix} x_J$$

Rearrange rows to give:

$$\begin{bmatrix} x_I' \\ x_J' \end{bmatrix} = \begin{bmatrix} S \\ D \end{bmatrix} x_J' = \begin{bmatrix} SD^{-1} \\ I \end{bmatrix} x_J'$$

(S and D are the same as above.  $B^{-1}R = SD^{-1}$ .)

For the dual:

$$\begin{aligned} [U_I \ U_J] &= U_I [I \ -A] + [0 \ C] \\ [U_I' \ U_J'] &= U_I' [B \ -R] + [C_I' \ C_J'] \\ [U_I' \ U_J'] &= U_I' [I \ -B^{-1}R] + [0 \ \bar{C}] \end{aligned}$$

where  $\bar{C} = C_J' + C_I' B^{-1}R$  and is the same as before. The inverse matrix  $B^{-1}$  is the product of elementary row operations;  $D^{-1}$  is the product of elementary column operations. Either one may be used to keep track of changes. LINOPT uses  $D^{-1}$  and generates coefficients and solutions from the original constraint coefficients by:

$$\begin{bmatrix} x_I \\ x_J \end{bmatrix} = \begin{bmatrix} A \\ I \end{bmatrix} D^{-1} x_J'$$

When a basic solution is changed,  $D^{-1}$  is updated by column operations. (We have ignored  $x_0$ : assume that  $0 \in K$  so that  $c$  is a row of  $\begin{bmatrix} A \\ I \end{bmatrix}$ )

The dual simplex algorithm works with dual-feasible basic solutions. Given a set  $J$  defining primary primal variables,  $J$  is altered by adding an index not in  $J$  and dropping an index in  $J$ : a secondary variable replaces a primary variable. The resulting changes in the constraint coefficients can be accomplished by Gauss-Jordan pivoting. The indices entering and leaving  $J$  are chosen in such a way that dual-feasibility is maintained and the objective function value does not increase. Proof of convergence can be found in any linear programming text.<sup>6</sup> The procedure is:

1. Identify violated constraints:  $I' = \{i \in K \sim J: x_i > b_i\}$ .
2. If  $I'$  is empty, stop: basic solution is optimal.
3. Pick (by some heuristic)  $k \in I'$ .
4. Identify constraints which can be dropped without being violated when  $x_k$  is set to  $b_k$ :  $J' = \{j \in J: a_{kj} > 0\}$ .
5. If  $J'$  is empty, stop: constraints are inconsistent.

<sup>6</sup> For example, Hadley, op. cit., or Simonard, op. cit.

6. Identify subset of  $J'$  corresponding to constraints for which dual feasibility is maintained when dropped:  $J'' = \{j \in J' : c_j/a_{kj} = \min_{j \in J'} (c_j/a_{kj})\}$ .
7. Pick (while applying anticycling criterion, if desired)  $\ell \in J''$ .
8. Update solution:  $J := J \cup \{k\} \sim \{\ell\}$ . Update inverse  $D^{-1}$  by column operations. Calculate new basic solution.
9. Go to 1.

The coefficients  $a_{kj}$  and  $c_j$  are those corresponding to the current index set  $J$ , not the original one in terms of which the problem is phrased, and are calculated by post-multiplying an original constraint matrix row (or objective row) by  $D^{-1}$ .

In the program the heuristic used in step 3 is to pick the most violated constraint. In step 7 a tie for  $\ell$  is broken randomly, a procedure which prevents cycling almost surely.

## CHAPTER 5

## EXAMPLES

TEST PROGRAM

A small test program to run the following examples is listed in Figure 2. The lines between the call to LINOPT and the call to TABLO merely do some cosmetic surgery on the output, replacing quantities near M in magnitude (actually those  $\geq \sqrt{M}$ ) by  $\pm R$  (machine infinities). Three examples are given, with NAMELIST inputs and the outputs from the program. Note that in all three, ROW and COL are defined to correspond to storage by rows, and the columns of the array A contain the rows of the constraint coefficient matrix.

EXAMPLE 1

This example is essentially the problem discussed in Section 1-3 of Hadley<sup>7</sup>, with slightly modified coefficients.

$$\text{Maximize } x_8 = 5.0 x_1 + 7.6 x_2 + 8.0 x_3 + 4.0 x_4$$

$$\text{subject to } x_1 \geq 0, x_2 \geq 0, x_3 \geq 0, x_4 \geq 0,$$

$$x_5 = 1.5 x_1 + 1.2 x_2 + 2.4 x_3 + 1.2 x_4 \leq 2100,$$

$$x_6 = 1.0 x_1 + 4.5 x_2 + 1.0 x_3 + 3.0 x_4 \leq 8000,$$

$$x_7 = 1.5 x_1 + 3.0 x_2 + 3.6 x_3 + 1.0 x_4 \leq 5000.$$

---

<sup>7</sup> Op. cit



## NAMELIST INPUT:

```

$IN
IOBJ = 8
M = 4,
N = 4,
MIN = .FALSE.,
INVERT = .TRUE.,
ITMAX = 1000,
EPS = 0.,
ROW = 0, 10, 20, 30,
COL = 1, 2, 3, 4,
A(1, 1) = 1.5, 1.2, 2.4, 1.2,
A(1, 2) = 1.0, 4.5, 1.0, 3.0,
A(1, 3) = 1.5, 3.0, 3.6, 1.0,
A(1, 4) = 5.0, 7.6, 8.0, 4.0,
BL = 4*0., 4*-1.E100,
BU = 4*1.E100, 2100., 8000., 5000., 1.E100,
K = 1, 2, 3, 4, 5, 6, 7, 8,
X = 4*0.,
$END

```

(Since the objective coefficients  $c_j$  are all nonzero for the initial tableau, it is not really necessary to preset  $x_1$ ,  $x_2$ ,  $x_3$  and  $x_4$ , as Example 2 will show).

## Output:

TABLEAU

I	BL(I)	x(I)	BU(I)	T(I, 1)	T(I, 3)	T(I, 5)	T(I, 7)
1	0.000	0.000	R	1.000	0.000	0.000	0.000
2	0.000	1625.000	R	-.125	-.800	-.417	.500
3	0.000	0.000	R	0.000	1.000	0.000	0.000
4	0.000	125.000	R	-1.125	-1.200	1.250	-.500
5	-R	2100.000	2100.000	0.000	.000	1.000	-.000
6	-R	7687.500	8000.000	-2.938	-6.200	1.875	.750
7	-R	5000.000	5000.000	-.000	.000	.000	1.000
8	-R	12850.000	R	-.450	-2.880	1.833	1.800

The objective variable,  $x(8)$ , is to be maximized. ITER = 10, IERR = 0.

The tableau gives information about the primary and secondary variables at the final iteration. The primary variables are  $x_1$ ,  $x_3$ ,  $x_5$  and  $x_7$ . The rows of the tableau give the coefficients of the variables expressed in terms of the primary variables. Thus,  $x_4 = -1.125 x_1 - 1.2 x_3 + 1.125 x_5 - .5 x_7$ . The dual variables are not printed explicitly but the nonzero ones can be obtained from the objective row:  $u_1 = -.450$ ,  $u_3 = -2.880$ ,  $u_5 = 1.833$ ,  $u_7 = 1.800$ . (For a minimization problem, these should be negated.)

EXAMPLE 2

This problem also comes from Hadley<sup>8</sup>. It is his Problem 8-5.

Minimize  $x_4 = 3x_1 - 2x_2 + 4x_3$   
 subject to  $x_1 \geq 0, x_2 \geq 0, x_3 \geq 0,$   
 $x_5 = 3x_1 + 5x_2 + 4x_3 \geq 7,$   
 $x_6 = 6x_1 + x_2 + 3x_3 \geq 4,$   
 $x_7 = 7x_1 - 2x_2 - x_3 \leq 10,$   
 $x_8 = x_1 - 2x_2 + 5x_3 \geq 3,$   
 $x_9 = 4x_1 + 7x_2 - 2x_3 \geq 2.$

Input:

```
$IN
IOBJ = 4,
M = 6,
N = 3,
MIN = . TRUE.,
INVERT = . TRUE.,
ITMAX = 1000,
EPS = 0.,
ROW = 0, 10, 20, 30, 40, 50,
COL = 1, 2, 3,
A(1, 1) = 3., -2., 4.,
A(1, 2) = 3., 5., 4.,
A(1, 3) = 6., 1., 3.,
A(1, 4) = 7., -2., -1.,
A(1, 5) = 1., -2., 5.,
A(1, 6) = 4., 7., -2.,
BL = 3*0., -1.E100, 7., 4., -1.E100, 3., 2.,
BU = 6*1.E100, 10., 2*1.E100,
K = 1,2,3,4,5,6,7,8,9,
$END
```

Output:

TABLEAU

I	BL(I)	X(I)	BU(I)	T(I, 1)	T(I, 5)	T(I, 8)
1	0.000	0.000	R	1.000	1.000	0.000
2	0.000	R	R	-.333	.152	-.121
3	0.000	R	R	-.333	.061	.152
4	-R	-R	R	2.333	-.061	.848
5	7.000	R	R	-.000	1.000	.000
6	4.000	R	R	4.667	.333	.333
7	-R	-R	10.000	8.000	-.364	.091
8	3.000	3.000	R	.000	0.000	1.000
9	2.000	R	R	2.333	.939	-1.152

THE OBJECTIVE VARIABLE, X( 4), IS TO BE MINIMIZED.  
 ITER = 3 IERR = 0

8. Ibid., p. 267.

This problem has an unbounded solution:  $x_5 = +\infty$  and the objective value is  $-\infty$ .

### EXAMPLE 3

This example illustrates the solution of a dual problem.

$$\begin{aligned} &\text{Minimize } \sum_{k=3}^9 |u_k| \\ &\text{subject to } \sum_{k=3}^9 u_k = 1, \\ &\quad \sum_{k=3}^9 k u_k = 1. \end{aligned}$$

(The indexing starts at 3 for convenience.) Since there is no unit matrix in the constraint coefficient matrix, we add artificial variables  $u_1$  and  $u_2$ , which must vanish at the solution:

$$\begin{aligned} u_1 + \sum_{k=3}^9 u_k &= 1, \\ u_2 + \sum_{k=3}^9 k u_k &= 1. \end{aligned}$$

Noting that  $|u_k| = \max \{-u_k, u_k\}$ , we can transform to the primal problem:

$$\begin{aligned} &\text{Maximize } x_{10} = x_1 + x_2 \\ &\text{subject to } -1 \leq x_i \leq 1, \quad i = 3, \dots, 9, \text{ where} \\ &\quad \begin{array}{ll} x_3 = x_1 + 3x_2, & x_4 = x_1 + 4x_2 \\ x_5 = x_1 + 5x_2, & x_6 = x_1 + 6x_2 \\ x_7 = x_1 + 7x_2, & x_8 = x_1 + 8x_2 \\ x_9 = x_1 + 9x_2. \end{array} \end{aligned}$$

The variables  $x_1$  and  $x_2$ , dual to artificial variables, are not constrained directly.

Input:

```
$IN
IOBJ = 10,
M = 8,
N = 2,
MIN = .FALSE.,
INVERT = .TRUE.,
ITMAX = 1000,
EPS = 0.,
ROW = 0, 10, 20, 30, 40, 50, 60, 70,
COL = 1, 2,
A(1, 1) = 1., 3.,
A(1, 2) = 1., 4.,
A(1, 3) = 1., 5.,
A(1, 4) = 1., 6.,
```

```

A(1, 5) = 1., 7.,
A(1, 6) = 1., 8.,
A(1, 7) = 1., 9.,
A(1, 8) = 1., 1.,
BL = 2*-1.E100, 7*-1., -1.E100,
BU = 2*1.E100, 7*-1., 1.E100.
K = 1,2,3,4,5,6,7,8,9,10,
X = 2*1.E100,
$END

```

Output:

I	BL(I)	X(I)	BU(I)	T(I, 3)	T(I, 9)
1	-R	2.000	R	1.500	-.500
2	-R	-.333	R	-.167	.167
3	-1.000	1.000	1.000	1.000	-.000
4	-1.000	.667	1.000	.833	.167
5	-1.000	.333	1.000	.667	.333
6	-1.000	.000	1.000	.500	.500
7	-1.000	-.333	1.000	.333	.667
8	-1.000	-.667	1.000	.167	.833
9	-1.000	-1.000	1.000	.000	1.000
10	-R	1.667	R	1.333	-.333

The solution is obtained from row 10:  $u_3 = 1.333$ ,  $u_9 = -.333$ ,  $u_4, \dots$ ,  $u_8 = 0$ . The minimal value is 1.667. (Obviously, the exact solution has  $u_3 = 4/3$ ,  $u_9 = -1/3$ .)

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PROGRAM TEST 73/74 OPT =1

PROGRAM TEST (INPUT , OUTPUT)

```

1  C
2  C
3  C
4  C
5  C
6  C
7  C
8  C
9  C
10 C
11 C
12 C
13 C
14 C
15 C
16 C
17 C
18 C
19 C
20 C
21 C
22 C
23 C
24 C
25 C
26 C
27 C
28 C

PROGRAM TEST (INPUT , OUTPUT)

TEST
LINE
LINE
LINE
LINE
TEST
LINE
LINE
LINE
LINE
TEST
TEST
TEST
TEST
MOD1
/XXXLP/
MOD1
MOD1
LINE
LINE
LINE

DIMENSION A(10,10), ROW (10), COL (10), BL(20), BU(20), K(20)
DIMENSION X(20), U(20), E (100), SCR(10), KORD(10)
INTEGER ROW, COL

COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITMAX, EPS, ITER, IERR
COMMON /XXXLP/ NPI, NPM, IPIV, JPIV, NEGV
COMMON /XXXLP/ BIGM
LOGICAL MIN, INVERT, NEGV

NAMELIST /IN/
1 IOBJ, M, N, MIN, INVERT, ITMAX, EPS,
2 A, ROW, COL, BL, BU, K, X

READ IN
CALL LINOPT(A,ROW,COL,BL,BU,K,X,U,E,SCR)
BIGM2 = SQRT(BIGM)
DO 20 I = 1, NPM
  IF (BL(I).LE.-BIGM2) BL(I) = ANEGINF
  IF (BU(I).GE.BIGM2) BU(I) = -ANEGINF
  IF (ABS(X(I)).GE.BIGM2) X(I) = %IGN(ANEGINF,X(I))
CONTINUE
CALL TABLO (A,ROW,COL,BL,BU,K,X,E,SCR,KORD)
PRINT*, IH
PRINT*, IOH ITER = , ITER, IOH IERR = , IERR
STOP
END

```

FIGURE 2 TEST PROGRAM

## CHAPTER 6

## LISTING

SUBROUTINE LINOPT(A,ROW,COL,BL,BU,K,X,U,E,SCR)	LINOPT	2
C	LINE	2
C-----	LINE	3
C	LINE	4
C LINEAR PROGRAMMING BY THE DUAL SIMPLEX ALGORITHM	LINOPT	4
C	LINOPT	5
C	LINOPT	6
C PROBLEM--	LINOPT	7
C	LINOPT	8
C MINIMIZE OR MAXIMIZE X(IOBJ) SUBJECT TO	LINOPT	9
C	LINOPT	10
C X(N+I) = SUM(J = 1,...,M) A(ROW(I)+COL(J)) * X(J),	LINOPT	11
C I = 1,...,M,	LINOPT	12
C	LINOPT	13
C BL(J) .LE. X(J) .LE. BU(J), J = 1,...,N+M.	LINOPT	14
C	LINOPT	15
C	LINOPT	16
C	LINOPT	17
C FURTHER DOCUMENTATION AND EXAMPLES OF USE CAN BE FOUND IN--	LINOPT	18
C	LINOPT	19
C NSWC TR 80-413, LINOPT, A FORTRAN ROUTINE FOR SOLVING	LINOPT	20
C LINEAR PROGRAMMING PROBLEMS, BY J.W. WINGATE.	LINOPT	21
C	LINOPT	22
C	LINOPT	23
C	LINOPT	24
C ARRAYS ARE PASSED AS FORMAL PARAMETERS, SIMPLE VARIABLES AS	LINOPT	25
C ELEMENTS OF THE COMMON BLOCK /XXXXLP/.	LINOPT	26
C	LINOPT	27
C INPUTS--THE FOLLOWING VARIABLES AND ARRAYS MUST BE DEFINED ON	LINOPT	28
C ENTRY	LINOPT	29
C	LINOPT	30
C IOBJ INDEX OF THE OBJECTIVE VARIABLE. (INTEGER)	LINOPT	31
C (NOTE THAT X(IOBJ) IS ALSO CONSIDERED AS	LINOPT	32
C A CONSTRAINED VARIABLE.)	LINOPT	33
C	LINOPT	34
C M NUMBER OF DEPENDENT VARIABLES. (INTEGER)	LINOPT	35
C N NUMBER OF INDEPENDENT VARIABLES. (INTEGER)	LINOPT	36
C	LINOPT	37
C MIN .TRUE. FOR MINIMIZATION, (LOGICAL)	LINOPT	38
C .FALSE. FOR MAXIMIZATION.	LINOPT	39
C	LINOPT	40

C	INVERT	.TRUE. IF THE INVERSE MATRIX E	(LOGICAL)	LINOPT	41
C		IS TO BE CALCULATED.		LINOPT	42
C		.FALSE. IF E IS ALREADY SET TO THE INVERSE FOR		LINOPT	43
C		THE BASIS DEFINED BY K. (FOR REOPTIMIZATION,		LINOPT	44
C		INVERT SHOULD BE .FALSE. UNLESS REINVERSION		LINOPT	45
C		IS DESIRED.)		LINOPT	46
C				LINOPT	47
C	ITMAX	MAXIMUM NUMBER OF ITERATIONS ALLOWED.	(INTEGER)	LINOPT	48
C		CONTROL IS RETURNED TO THE CALLING		LINOPT	49
C		PROGRAM AFTER ITMAX ITERATIONS.		LINOPT	50
C				LINOPT	51
C	EPS	ZERO TOLERANCE. CONSTRAINT VIOLATIONS	(REAL)	LINOPT	52
C		OR TABLEAU ENTRIES .LE. EPS IN MAGNITUDE		LINOPT	53
C		ARE TREATED AS ZERO.		LINOPT	54
C				LINOPT	55
C	A	ARRAY CONTAINING THE COEFFICIENT MATRIX.	(REAL)	LINOPT	56
C	ROW	ROW INDEX ARRAY.	(INTEGER)	LINOPT	57
C	COL	COLUMN INDEX ARRAY.	(INTEGER)	LINOPT	58
C		THE COEFFICIENT OF X(J) IN THE EQUATION		LINOPT	59
C		FOR X(N+I) IS A(ROW(I)+COL(J)).		LINOPT	60
C		EITHER (CASE 1)		LINOPT	61
C		ONE HAS VECTORS AROW1,...,AROWM WITH		LINOPT	62
C		AROWI(COL(J)) THE COEFFICIENT OF X(J)		LINOPT	63
C		IN THE EQUATION FOR X(N+I), IN WHICH CASE		LINOPT	64
C		ROW(I) = LOCF(AROWI) - LOCF(A), I = 1,...,M,		LINOPT	65
C		OR (CASE 2)		LINOPT	66
C		ONE HAS VECTORS ACOL1,...,ACOLN WITH		LINOPT	67
C		ACOLJ(ROW(I)) THE COEFFICIENT OF X(J)		LINOPT	68
C		IN THE EQUATION FOR X(N+I), IN WHICH CASE		LINOPT	69
C		COL(J) = LOCF(ACOLJ) - LOCF(A), J = 1,...,N.		LINOPT	70
C		(E.G. IF A IS DIMENSIONED FOR MM ROWS		LINOPT	71
C		AND THE COEFFICIENT MATRIX IS STORED IN		LINOPT	72
C		THE FIRST M ROWS AND N COLUMNS OF A (CASE 2),		LINOPT	73
C		ROW(I) = I, I = 1,...,M,		LINOPT	74
C		COL(J) = (J-1)*MM, J = 1,...,N,		LINOPT	75
C		WHILE IF THE COEFFICIENT MATRIX IS STORED		LINOPT	76
C		TRANSPOSED IN THE FIRST N ROWS AND M COLUMNS		LINOPT	77
C		(CASE 1),		LINOPT	78
C		ROW(I) = (I-1)*MM, I = 1,...,M,		LINOPT	79
C		COL(J) = J, J = 1,...,N.		LINOPT	80
C		ROW AND COL MAY BE PERMUTED IN ANY CONVENIENT		LINOPT	81
C		WAY.)		LINOPT	82
C				LINOPT	83
C	BL	ARRAY OF LOWER BOUNDS.	(REAL)	LINOPT	84
C	BU	ARRAY OF UPPER BOUNDS.	(REAL)	LINOPT	85
C				LINOPT	86
C	K	BASIC SOLUTION KEY.	(INTEGER)	LINOPT	87
C		K, IN CONJUNCTION WITH X, SPECIFIES A		LINOPT	88
C		PARTICULAR BASIC SOLUTION. THE EQUATIONS		LINOPT	89
C		RELATING X(N+I), I = 1,...,M TO		LINOPT	90
C		X(J), J = 1,...,N (THE CONSTRAINT EQUATIONS)		LINOPT	91
C		CAN BE SOLVED FOR VARIOUS COMBINATIONS OF		LINOPT	92

C		M VARIABLES (SECONDARY VARIABLES) IN TERMS	LINOPT	93
C		OF THE REMAINING N VARIABLES (PRIMARY	LINOPT	94
C		VARIABLES). K, A PERMUTATION OF (1,...,N+M),	LINOPT	95
C		SPECIFIES SUCH A PARTITION INTO PRIMARY AND	LINOPT	96
C		SECONDARY VARIABLES. K(1),...,K(N) ARE THE	LINOPT	97
C		INDICES OF THE PRIMARY VARIABLES. K(N+1),...,	LINOPT	98
C		K(N+M) ARE THE INDICES OF THE SECONDARY	LINOPT	99
C		VARIABLES. FOR THE DUAL VARIABLES U(J),	LINOPT	100
C		J = 1,...,N+M, PRIMARY AND SECONDARY INDICES	LINOPT	101
C		SWITCH ROLES, U(K(N+1)),...,U(K(N+M)) BEING	LINOPT	102
C		PRIMARY. A BASIC SOLUTION IS SPECIFIED BY	LINOPT	103
C		SETTING EACH PRIMAL PRIMARY VARIABLE TO	LINOPT	104
C		EITHER OF ITS BOUNDS AND EACH DUAL PRIMARY	LINOPT	105
C		VARIABLE TO ZERO. THE INPUT VALUES OF THE	LINOPT	106
C		PRIMAL PRIMARY VARIABLES ARE SWITCHED TO THE	LINOPT	107
C		OPPOSITE BOUND IF NECESSARY IN ORDER TO CREATE	LINOPT	108
C		A DUAL-FEASIBLE BASIC SOLUTION.	LINOPT	109
C			LINOPT	110
C	X	PRIMAL SOLUTION ARRAY. (REAL)	LINOPT	111
C		X(K(J)) MUST BE SET TO EITHER BL(K(J)) OR	LINOPT	112
C		BU(K(J)), J = 1,...,N. THESE ARE DEFAULT	LINOPT	113
C		VALUES TO BE USED WHEN A VANISHING U(K(J))	LINOPT	114
C		MAKES X(K(J)) INDETERMINATE IN SETTING UP	LINOPT	115
C		A DUAL-FEASIBLE SOLUTION.	LINOPT	116
C			LINOPT	117
C		OUTPUTS--THE FOLLOWING VARIABLES AND ARRAYS ARE DEFINED	LINOPT	118
C		OR REDEFINED ON EXIT	LINOPT	119
C			LINOPT	120
C	ITER	NUMBER OF ITERATIONS SINCE THE LAST (INTEGER)	LINOPT	121
C		INVERSION.	LINOPT	122
C			LINOPT	123
C	IERR	ERROR FLAG. (INTEGER)	LINOPT	124
C		IERR = 0--OPTIMUM FOUND.	LINOPT	125
C		1--INCONSISTENT CONSTRAINTS.	LINOPT	126
C		2--ITERATION LIMIT REACHED.	LINOPT	127
C		3--INVERSION FAILED (BAD INITIAL BASIS).	LINOPT	128
C			LINOPT	129
C	K	BASIC SOLUTION KEY, (INTEGER)	LINOPT	130
C		SET FOR THE CURRENT BASIS.	LINOPT	131
C			LINOPT	132
C	X	PRIMAL SOLUTION ARRAY. (REAL)	LINOPT	133
C			LINOPT	134
C	U	DUAL SOLUTION ARRAY. (REAL)	LINOPT	135
C		U(J) IS THE DUAL VARIABLE (LAGRANGE	LINOPT	136
C		MULTIPLIER) FOR THE CONSTRAINTS ON X(J).	LINOPT	137
C		IT IS POSITIVE IF THE UPPER BOUND IS ACTIVE.	LINOPT	138
C		NEGATIVE IF THE LOWER BOUND IS ACTIVE.	LINOPT	139
C			LINOPT	140
C	E	INVERSE MATRIX ARRAY. (REAL)	LINOPT	141
C		$X(I) = \sum_{J=1, \dots, N} E(I, J) * X(K(J)),$	LINOPT	142
C		$I = 1, \dots, N.$	LINOPT	143



C			LINOPT	144
C	SCR	(ALIAS AROW IN SUBROUTINES) SCRATCH ARRAY.	LINOPT	145
C			LINOPT	146
C		-----	LINOPT	147
C			LINOPT	148
C	MINIMUM DECLARED ARRAY SIZES--		LINOPT	149
C			LINOPT	150
C	A	M * N	LINOPT	151
C	ROW	M	LINOPT	152
C	COL	N	LINOPT	153
C	BL	M + N	LINOPT	154
C	BU	M + N	LINOPT	155
C	K	M + N	LINOPT	156
C	X	M + N	LINOPT	157
C	U	M + N	LINOPT	158
C	E	M * N	LINOPT	159
C	SCR	N	LINOPT	160
C			LINOPT	161
C		-----	LINOPT	162
C			LINOPT	163
C	SUBROUTINE TABLO (Q.V.) PRINTS THE FULL EXPLICIT TABLEAU.		LINOPT	164
C	IT IS NOT CALLED THROUGH LINOPT AND MUST BE CALLED SEPARATELY.		LINOPT	165
C			LINE	2
C			LINE	3
C			LINE	4
C	DIMENSION BL(1), BU(1), K(1), X(1), U(1), SCR(1)		LINOPT	167
C			LINOPT	168
C	COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITHAX, EPS, ITER, IERR	/XXXLP/	2	
C	COMMON /XXXLP/ NPI, NPM, IPIV, JPIV, NEGV	/XXXLP/	3	
C	COMMON /XXXLP/ BIGM	/XXXLP/	4	
C	LOGICAL MIN, INVERT, NEGV	/XXXLP/	5	
C		LINE	2	
C		LINE	3	
C		LINE	4	
C	THE VARIABLE BIGM REPRESENTS A VERY LARGE NUMBER. THE DEFAULT	LINOPT	171	
C	VALUE IS 1.E100. THE USER MAY RESET THIS VALUE IF SO DESIRED.	LINOPT	172	
C	BIGM OR -BIGM MAY BE USED TO FILL IN MISSING UPPER OR LOWER	LINOPT	173	
C	BOUNDS.	LINOPT	174	
C		LINOPT	175	
C	DATA BIGM /1.E100/	LINOPT	176	
C		LINE	2	
C		LINE	3	
C		LINE	4	
C	NPI = N + 1	LINOPT	178	
C	NPM = N + M	LINOPT	179	
C	IF (.NOT. INVERT) GO TO 10	LINOPT	180	
C	CALL SETINV(A,ROW,COL,K,E,SCR)	LINOPT	181	
C	IF (IERR.EQ.3) RETURN	LINOPT	182	
C	10 CONTINUE	LINOPT	183	
C	CALL GETROW(A,ROW,COL,E,IOBJ,SCR)	LINOPT	184	
C	DO 50 J = 1, N	LINOPT	185	
C	KJ = K(1)	LINOPT	186	

	IF (MIN) SCR(J) = -SCR(J)	LINOPT	187
	U(KJ) = SCR(J)	LINOPT	188
	IF (U(KJ)) 20, 40, 30	LINOPT	189
C	NEGATIVE	LINOPT	190
20	CONTINUE	LINOPT	191
	X(KJ) = BL(KJ)	LINOPT	192
	GO TO 40	LINOPT	193
C	POSITIVE	LINOPT	194
30	CONTINUE	LINOPT	195
	X(KJ) = BU(KJ)	LINOPT	196
40	CONTINUE	LINOPT	197
50	CONTINUE	LINOPT	198
	DO 60 J = NP1, NPM	LINOPT	199
	U(K(J)) = 0.	LINOPT	200
60	CONTINUE	LINOPT	201
	CALL PSOL(A,ROW,COL,K,X,E)	LINOPT	202
	CALL DSIMP(A,ROW,COL,BL,BU,X,X,U,E,SCR)	LINOPT	203
	IF (IERR.NE.0) GO TO 110	LINOPT	204
C	ROUND X-VALUES WITHIN EPS OF BOUNDS	LINOPT	205
	DO 100 I = 1, NPM	LINOPT	206
	IF (ABS(X(I)-BL(I)).LE.EPS) X(I) = BL(I)	LINOPT	207
	IF (ABS(X(I)-BU(I)).LE.EPS) X(I) = BU(I)	LINOPT	208
100	CONTINUE	LINOPT	209
110	CONTINUE	LINOPT	210
	RETURN	LINOPT	211
	END	LINOPT	212

SUBROUTINE DSIMP(A,ROW,COL,BL,BU,K,X,U,E,AROW)	DSIMP	2
C	LINE	2
C-----	LINE	3
C	LINE	4
C DUAL SIMPLEX ALGORITHM	DSIMP	4
C	LINE	2
C-----	LINE	3
C	LINE	4
DIMENSION BL(1), BU(1), K(1), X(1), U(1), AROW(1)	DSIMP	6
C	DSIMP	7
COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITHAX, EPS, ITER, IERR	/XXXLP/	2
COMMON /XXXLP/ NPI, NPH, IPIV, JPIV, NEGV	/XXXLP/	3
COMMON /XXXLP/ BIGH	/XXXLP/	4
LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C	LINE	2
C-----	LINE	3
C	LINE	4
IERR = 2	DSIMP	10
C WHEN ITHAX.LT.1 THE LOOP IS PARTIALLY EXECUTED	DSIMP	11
DO 100 II = 1, ITHAX	DSIMP	12
CALL PIVROW(BL,BU,K,X)	DSIMP	13
IF (IPIV.GT.0) GO TO 10	DSIMP	14
C NO PIVOT ROW INDICATES THAT X IS OPTIMAL	DSIMP	15
IERR = 0	DSIMP	16
RETURN	DSIMP	17
10 CONTINUE	DSIMP	18
KROW = K(IPIV)	DSIMP	19
CALL GETROW(A,ROW,COL,E,KROW,AROW)	DSIMP	20
CALL PIVCOL(BL,BU,K,X,U,AROW)	DSIMP	21
IF (JPIV.GT.0) GO TO 40	DSIMP	22
C NO PIVOT COLUMN INDICATES THAT THE CONSTRAINTS	DSIMP	23
C ARE INCONSISTENT	DSIMP	24
IERR = 1	DSIMP	25
RETURN	DSIMP	26
40 CONTINUE	DSIMP	27
IF (ITHAX.LT.1) RETURN	DSIMP	28
C NEW SOLUTION KEY	DSIMP	29
K(IPIV) = K(JPIV)	DSIMP	30
K(JPIV) = KROW	DSIMP	31
CALL NEWINV(E,AROW)	DSIMP	32
C NEW DUAL SOLUTION	DSIMP	33
CALL GETROW(A,ROW,COL,E,IOBJ,AROW)	DSIMP	34
DO 70 J = 1, N	DSIMP	35
IF (MIN) AROW(J) = -AROW(J)	DSIMP	36
U(K(J)) = AROW(J)	DSIMP	37
70 CONTINUE	DSIMP	38
U(K(IPIV)) = 0.	DSIMP	39
C NEW PRIMAL SOLUTION	DSIMP	40
X(KROW) = BU(KROW)	DSIMP	41
IF (NEGV) X(KROW) = BL(KROW)	DSIMP	42
CALL PSOL(A,ROW,COL,K,X,E)	DSIMP	43
ITER = ITER + 1	DSIMP	44
100 CONTINUE	DSIMP	45

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RETURN  
END

DSIMP	45
DSIMP	47

SUBROUTINE PIVROW(BL,BU,K,X)	PIVROW	2
C	LINE	2
C-----	LINE	3
C	LINE	4
C PIVOT ROW SELECTION	PIVROW	4
C	LINE	2
C-----	LINE	3
C	LINE	4
C DIMENSION BL(I), BU(I), K(I), X(I)	PIVROW	6
C	PIVROW	7
COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITHAX, EPS, ITER, IERR	/XXXLP/	2
COMMON /XXXLP/ NPI, NPM, IPIV, JPIV, NEGV	/XXXLP/	3
COMMON /XXXLP/ BIGH	/XXXLP/	4
LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C	LINE	2
C-----	LINE	3
C	LINE	4
IPIV = 0	PIVROW	10
IF (NPM.LT.NPI) RETURN	PIVROW	11
VIOL = 0.	PIVROW	12
DO 50 II = NPI, NPM	PIVROW	13
I = K(II)	PIVROW	14
C CHECK CONSTRAINTS ON X(I)	PIVROW	15
D = X(I) - BL(I)	PIVROW	16
IF (D.GE.-EPS) GO TO 10	PIVROW	17
D = -D	PIVROW	18
IF (VIOL.GT.D) GO TO 40	PIVROW	19
VIOL = D	PIVROW	20
IPIV = II	PIVROW	21
NEGV = .TRUE.	PIVROW	22
GO TO 40	PIVROW	23
10 CONTINUE	PIVROW	24
D = X(I) - BU(I)	PIVROW	25
IF (D.LE.EPS) GO TO 30	PIVROW	26
IF (VIOL.GT.D) GO TO 40	PIVROW	27
VIOL = D	PIVROW	28
IPIV = II	PIVROW	29
NEGV = .FALSE.	PIVROW	30
30 CONTINUE	PIVROW	31
40 CONTINUE	PIVROW	32
50 CONTINUE	PIVROW	33
RETURN	PIVROW	34
END	PIVROW	35

SUBROUTINE PIVCOL(BL,BU,K,X,U,AROW)	PIVCOL	2
C	LINE	2
C-----	LINE	3
C	LINE	4
C PIVDT COLUMN SELECTION	PIVCOL	4
C	LINE	2
C-----	LINE	3
C	LINE	4
C DIMENSION BL(1), BU(1), K(1), X(1), U(1), AROW(1)	PIVCOL	6
C	PIVCOL	7
COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITMAX, EPS, ITER, IERR	/XXXLP/	2
COMMON /XXXLP/ NPI, NPM, IPIV, JPIV, NEGV	/XXXLP/	3
COMMON /XXXLP/ BIGH	/XXXLP/	4
LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C	LINE	2
C-----	LINE	3
C	LINE	4
JPIV = 0	PIVCOL	10
W = BIGH	PIVCOL	11
DO 30 JJ = 1, N	PIVCOL	12
J = K(JJ)	PIVCOL	13
AA = AROW(JJ)	PIVCOL	14
IF (NEGV) AA = -AA	PIVCOL	15
IF (AA.GE.0. .AND. X(J).EQ.BL(J)) GO TO 20	PIVCOL	16
IF (AA.LE.0. .AND. X(J).EQ.BU(J)) GO TO 20	PIVCOL	17
R = U(J)/AA	PIVCOL	18
IF (R.GT.W) GO TO 10	PIVCOL	19
IF (R.EQ.W .AND. RANF(AA).GT.0.5) GO TO 10	PIVCOL	20
JPIV = JJ	PIVCOL	21
W = R	PIVCOL	22
10 CONTINUE	PIVCOL	23
20 CONTINUE	PIVCOL	24
30 CONTINUE	PIVCOL	25
RETURN	PIVCOL	26
END	PIVCOL	27

	SUBROUTINE GETROW(A,ROW,COL,E,KROW,AROW)	GETROW	1
C		LINE	2
C	-----	LINE	3
C		LINE	4
C	GENERATION OF CONSTRAINT COEFFICIENTS FOR THE CURRENT BASIS	GETROW	4
C		LINE	2
C	-----	LINE	3
C		LINE	4
	DIMENSION A(1), ROW(1), COL(1), E(1), AROW(1)	GETROW	5
	INTEGER ROW, COL	GETROW	7
C		GETROW	3
	COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITHAX, EPS, ITER, IERR	/XXXLP/	2
	COMMON /XXXLP/ NPI, NPM, IPIV, JPIV, NEGV	/XXXLP/	3
	COMMON /XXXLP/ BIGH	/XXXLP/	4
	LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C		LINE	2
C	-----	LINE	3
C		LINE	4
	IF (KROW.GT.N) GO TO 20	GETROW	11
C	ORIGINAL INDEPENDENT VARIABLE. GET ROW KROW OF THE INVERSE.	GETROW	12
	JJ = 0	GETROW	13
	DO 10 J = 1, N	GETROW	14
	AROW(J) = E(KROW+JJ)	GETROW	15
	IF (ABS(AROW(J)).LE.EPS) AROW(J) = 0.	GETROW	16
	JJ = JJ + N	GETROW	17
10	CONTINUE	GETROW	18
	GO TO 50	GETROW	19
20	CONTINUE	GETROW	20
C	ORIGINAL DEPENDENT VARIABLE.	GETROW	21
C	MULTIPLY ORIGINAL ROW BY THE INVERSE.	GETROW	22
	KK = ROW(KROW-N)	GETROW	23
	JJ = 0	GETROW	24
	DO 40 J = 1, N	GETROW	25
	AROW(J) = 0.	GETROW	26
	DO 30 I = 1, N	GETROW	27
	AROW(J) = AROW(J) + A(KK+COL(I))*E(I+JJ)	GETROW	28
30	CONTINUE	GETROW	29
	IF (ABS(AROW(J)).LE.EPS) AROW(J) = 0.	GETROW	30
	JJ = JJ + N	GETROW	31
40	CONTINUE	GETROW	32
50	CONTINUE	GETROW	33
	RETURN	GETROW	34
	END	GETROW	35

	SUBROUTINE PSOL(A,ROW,COL,K,X,E)	PSOL	2
C		LINE	2
C	-----	LINE	3
C		LINE	4
C	PRIMAL SOLUTION	PSOL	4
C		LINE	2
C	-----	LINE	3
C		LINE	4
	DIMENSION A(1), ROW(1), COL(1), K(1), X(1), E(1)	PSOL	6
	INTEGER ROW, COL	PSOL	7
C		PSOL	8
	COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITHAX, EPS, ITER, IERR	/XXXLP/	2
	COMMON /XXXLP/ NP1, NPM, IPIV, JPIV, NEGV	/XXXLP/	3
	COMMON /XXXLP/ BIGH	/XXXLP/	4
	LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C		LINE	2
C	-----	LINE	3
C		LINE	4
	DO 30 I = NP1, NPM	PSOL	11
	KI = K(I)	PSOL	12
	IF (KI.GT.N) GO TO 20	PSOL	13
	X(KI) = 0.	PSOL	14
	JJ = 0	PSOL	15
	DO 10 J = 1, N	PSOL	16
	X(KI) = X(KI) + E(KI+JJ) * X(K(J))	PSOL	17
	JJ = JJ + N	PSOL	18
10	CONTINUE	PSOL	19
20	CONTINUE	PSOL	20
30	CONTINUE	PSOL	21
	DO 60 I = NP1, NPM	PSOL	22
	KI = K(I)	PSOL	23
	IF (KI.LE.N) GO TO 50	PSOL	24
	X(KI) = 0.	PSOL	25
	KK = ROW(KI-N)	PSOL	26
	DO 40 J = 1, N	PSOL	27
	X(KI) = X(KI) + A(KK+COL(J)) * X(J)	PSOL	28
40	CONTINUE	PSOL	29
50	CONTINUE	PSOL	30
60	CONTINUE	PSOL	31
	RETURN	PSOL	32
	END	PSOL	33



SUBROUTINE SETINV(A,ROW,COL,K,E,AROW)	SETINV	2
C	LINE	2
C-----	LINE	3
C	LINE	4
C INITIAL INVERSE	SETINV	4
C	LINE	2
C-----	LINE	3
C	LINE	4
C DIMENSION K(1), E(1), AROW(1)	SETINV	6
C	SETINV	7
COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITMAX, EPS, ITER, IERR	/XXXLP/	2
COMMON /XXXLP/ NPI, NPM, IPIV, JPIV, NEGV	/XXXLP/	3
COMMON /XXXLP/ BIGM	/XXXLP/	4
LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C	LINE	2
C-----	LINE	3
C	LINE	4
C SET E TO THE IDENTITY	SETINV	10
JJ = 0	SETINV	11
DO 20 J = 1, N	SETINV	12
DO 10 I = 1, N	SETINV	13
E(I+JJ) = 0.	SETINV	14
10 CONTINUE	SETINV	15
E(J+JJ) = 1.	SETINV	16
JJ = JJ + N	SETINV	17
20 CONTINUE	SETINV	18
C GENERATE INITIAL INVERSE	SETINV	19
DO 30 J = 1, N	SETINV	20
K(J) = -K(J)	SETINV	21
30 CONTINUE	SETINV	22
DO 90 JJ = 1, N	SETINV	23
DO 40 J = 1, N	SETINV	24
IF (K(J).LT.0) GO TO 50	SETINV	25
40 CONTINUE	SETINV	26
50 CONTINUE	SETINV	27
KROW = -K(J)	SETINV	28
CALL GETROW(A,ROW,COL,E,KROW,AROW)	SETINV	29
ROWMAX = 0.	SETINV	30
DO 70 L = 1, N	SETINV	31
TEST = ABS(AROW(L))	SETINV	32
IF (K(L).GT.0 .OR. TEST.LT.ROWMAX) GO TO 60	SETINV	33
ROWMAX = TEST	SETINV	34
JPIV = L	SETINV	35
60 CONTINUE	SETINV	36
70 CONTINUE	SETINV	37
IF (ROWMAX.GT.0.) GO TO 80	SETINV	38
IERR = 3	SETINV	39
RETURN	SETINV	40
80 CONTINUE	SETINV	41

K(J) = K(JPIV)	SETINV	42
K(JPIV) = KROW	SETINV	43
CALL NEWINV(E,AROW)	SETINV	44
90 CONTINUE	SETINV	45
ITER = 0	SETINV	46
RETURN	SETINV	47
END	SETINV	48

C	SUBROUTINE NEWINV(E,AROW)	NEWINV	2
C	-----	LINE	2
C		LINE	3
C		LINE	4
C	INVERSE UPDATE BY COLUMN OPERATIONS	NEWINV	4
C	-----	LINE	2
C		LINE	3
C		LINE	4
C	DIMENSION E(1), AROW(1)	NEWINV	6
C		NEWINV	7
	COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITHAX, EPS, ITER, IERR	/XXXLP/	2
	COMMON /XXXLP/ NP1, NPM, IPIV, JPIV, NEGV	/XXXLP/	3
	COMMON /XXXLP/ BIGH	/XXXLP/	4
	LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C	-----	LINE	2
C		LINE	3
C		LINE	4
	JJPIV = (JPIV-1)*N	NEWINV	10
	DO 20 I = 1, N	NEWINV	11
	EPIV = E(I+JJPIV)/AROW(JPIV)	NEWINV	12
	JJ = 0	NEWINV	13
	DO 10 J = 1, N	NEWINV	14
	E(I+JJ) = E(I+JJ) - EPIV*AROW(J)	NEWINV	15
	JJ = JJ + N	NEWINV	16
10	CONTINUE	NEWINV	17
	E(I+JJPIV) = EPIV	NEWINV	18
20	CONTINUE	NEWINV	19
	RETURN	NEWINV	20
	END	NEWINV	21

SUBROUTINE TABLO(A,ROW,COL,BL,BU,K,X,E,SCR,KORD)		TABLO	2
C		LINE	2
C	-----	LINE	3
C		LINE	4
C	TABLEAU PRINTOUT	TABLO	4
C		TABLO	5
C	KORD IS AN ARRAY OF LENGTH AT LEAST N USED FOR REORDERING	TABLO	6
C	K(1),...,K(N) IN ASCENDING ORDER.	TABLO	7
C	SEE LINOPT FOR DESCRIPTIONS OF THE OTHER PARAMETERS.	TABLO	8
C		TABLO	9
C	LINOPT MUST HAVE BEEN CALLED BEFORE CALLING TABLO.	TABLO	10
C		LINE	2
C	-----	LINE	3
C		LINE	4
C	DIMENSION A(1), ROW(1), COL(1), BL(1), BU(1), K(1), X(1), E(1)	TABLO	12
	DIMENSION SCR(1), KORD(1)	TABLO	13
	INTEGER ROW, COL	TABLO	14
C		TABLO	15
	COMMON /XXXLP/ IOBJ, M, N, MIN, INVERT, ITHAX, EPS, ITER, IERR	/XXXLP/	2
	COMMON /XXXLP/ NPI, NPM, IPIV, JPIV, NEGV	/XXXLP/	3
	COMMON /XXXLP/ BIGN	/XXXLP/	4
	LOGICAL MIN, INVERT, NEGV	/XXXLP/	5
C		LINE	2
C	-----	LINE	3
C		LINE	4
	1 FORMAT (1H1//T55,*T A B L E A U*//1X,* I *,5X,*BL(I)*,	TABLO	18
	/ 6X,*X(I)*,5X,*BU(I)*,1X,10A10/(36X,10A10))	TABLO	19
	2 FGMAT (1H0,I3,1X,3F10.3,1X,10F10.3/(36X,10F10.3))	TABLO	20
	3 FORMAT (2X,*T(I,*,I3,*))	TABLO	21
	4 FORMAT (///1H0,*THE OBJECTIVE VARIABLE, X(*,I3,*), IS TO BE *,A10)	TABLO	22
C		LINE	2
C	-----	LINE	3
C		LINE	4
	DO 110 J = 1, N	TABLO	24
	KORD(J) = J	TABLO	25
110	CONTINUE	TABLO	26
	DO 130 J = 1, N	TABLO	27
	JMIN = J	TABLO	29
	DO 120 JJ = J, N	TABLO	29
	IF (K(KORD(JJ)).LT.K(KORD(JMIN))) JMIN = JJ	TABLO	30
120	CONTINUE	TABLO	31
	KTEMP = KORD(J)	TABLO	32
	KORD(J) = KORD(JMIN)	TABLO	33
	KORD(JMIN) = KTEMP	TABLO	34
130	CONTINUE	TABLO	35
	DO 10 J = 1, N	TABLO	36
	ENCODE (10,3,SCR(J)) K(KORD(J))	TABLO	37
10	CONTINUE	TABLO	38
	PRINT 1, (SCR(J), J = 1, N)	TABLO	39

DO 20 I = 1, NPH	TABLO	40
CALL GETROW(A,ROW,COL,E,I,SCR)	TABLO	41
PRINT 2, I, BL(I), X(I), BU(I), (SCR(KORD(J)), J = 1, N)	TABLO	42
20 CONTINUE	TABLO	43
OPT = 10HMAXIMIZED.	TABLO	44
IF (MIN) OPT = 10HMINIMIZED.	TABLO	45
PRINT 4, IOBJ, OPT	TABLO	46
RETURN	TABLO	47
END	TABLO	48

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